Adaptive loss aversion and market experience*

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Abstract

This paper develops a new behavioral model of how experience affects willingness to trade called adaptive loss aversion. In the model, agents do not recognize that others have different information. Loss aversion makes them cautious. When trading, this protects them from being exploited by better-informed traders. The degree of loss aversion λ is adjusted in response to experience and carries over between games. When outcomes are better than anticipated, λ decreases; when outcomes are worse than anticipated, it increases. A repeated market experiment with symmetric and asymmetric information is used to test the model. The data are noisier than anticipated but some of the model's main predictions are supported. A structural version of the model is estimated using the experimental data and data from two previous experiments on the winner's curse. A range of other behavioral game theory models is also estimated using the same data and the fit of the models is compared.

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This paper introduces adaptive loss aversion (ALA). It is a model of two aspects of trading behavior in settings where payoffs can depend on one's own actions, the actions of others and the state of nature. First, how people behave when they do not know the joint distribution of actions and states. Second, how people adjust this behavior in response to experienced outcomes. It contrasts with standard game theory, where agents have correct beliefs about the distribution of other's actions and states of nature. With such correct beliefs, the outcomes of trading will be on average as anticipated. Without correct beliefs, however, outcomes from trading can be surprising. They can systematically differ from what traders anticipated.

ALA is motivated by two lines of research. First, many studies have found that willingness-to-accept (WTA) valuations exceed willingness-to-pay (WTP) valuations.[1] This gap between WTA and WTP is an anomaly for standard economic theory. A consequence of the gap is that people are less willing to trade than standard theory predicts. A natural question is do the incentives and experience provided by markets eliminate the gap? When traders repeatedly buy or sell items in laboratory markets, the WTA/WTP gap often decays as traders gain market experience. More details are in Section 1. List (2003, Experiment 4) has found similar results in a field experiment using subjects recruited at a sportscard market. Those with relatively less intense trading experience exhibit the gap while those with relatively more intense trading experience do not. Together, these studies show that (a) market experience acquired in the lab and (b) certain market experience acquired in naturally occurring markets can be sufficient to eliminate the gap.

Second, a separate line of research has found substantial evidence that people do not behave optimally in games with asymmetric information. One example of this is behavior in the "acquiring a company task". In this game, a buyer makes a take-it-or-leave-it offer to a seller for a company that is worth v to the seller and $1.5v$ to the buyer. The value v is only known to the seller and is uniformly distributed between 0 and 100. In the Nash equilibrium of the game, the buyer bids zero. Despite this, Samuelson and Bazerman (1985) found most buyers bid between 50 and 75 and later studies have found this result is surprisingly robust (see Grosskopf, Bereby-Meyer and Bazerman (2007) and Bereby-Meyer and Grosskopf (2008)). Another example is bidding in experimental common value auctions. Suppose the common value of an item is the sum of bidders' private signals. In a symmetric Nash equilibrium, bidders recognize that winning the auction implies opponents had lower signals and shade their bids accordingly. In experiments, bidders seem not to account for this and so frequently fall prey to the winner's curse (see Kagel and Levin (2002) for many of the papers).

The model proposed in this paper, ALA, brings together these two lines of research. How ALA fits with the literature is described in Section 1. Features that distinguish ALA from earlier theories are that the effects of experience can carry over between games with different structures and that it

[1] WTP is the maximum a person would be willing to pay to secure an item. WTA is the minimum a person owning the item would be willing to accept to give it up. The WTA/WTP gap has been found in studies that use incentive-compatible elicitation mechanisms and control for income and substitution effects (e.g. Bateman et al., 1997). Reviews of WTA/WTP studies can be found in Horowitz and McConnell (2002), Brown and Gregory (1999), and Sayman and Onculer (2005).

can be applied to games in which the payoffs from unplayed actions are not available. The model is developed in Section 2. ALA has three aspects. First, it is assumed agents estimate the payoffs from trading using a simplified model of other's behavior rather than using knowledge of the joint distribution of other's actions and states of nature. Second, agents are loss averse when estimating the payoffs from trading. In naturally occurring settings, this loss aversion protects them from being exploited by better-informed traders. Third, after trading, agents compare the realized payoffs to the payoffs anticipated prior to trading. When payoffs are better than anticipated, agents become less loss averse and more willing to trade. Conversely, when they are worse, the agents become more loss averse and less willing to trade. One could think of this as an example of the *surprise-triggers-change* regularity which has been found to occur in a range of settings (Erev and Haruvy, 2016). A neurological explanation of this type of adaptive behavior has been suggested by Schultz, Dayan and Montague (1997).

The degree of loss aversion changing can account for some of the main results of WTA/WTP experiments. In ALA, agents do not recognize that others may have different information so perceive settings with symmetric and asymmetric information as equivalent. In settings with asymmetric information, the less informed will tend to receive worse than anticipated payoffs, causing loss aversion to increase. Conversely, settings with symmetric information will tend to deliver better than anticipated payoffs, causing it to decrease. Assuming experiment subjects encounter some situations with asymmetric information in their everyday lives, they will be somewhat loss averse when they enter the lab. In standard WTA/WTP experiments, there is no asymmetric information, hence trading gives better than anticipated payoffs. As a consequence, subjects become less loss averse, causing the WTA/WTP gap to decay.

The predictions of ALA were explored using the results of a repeated market experiment with 208 subjects. The experiment is described in Section 3. It had two parts. In each part, subjects bought or sold lotteries in a Vickrey auction for ten rounds under either symmetric or asymmetric information. Section 4 presents predictions of standard game theory and ALA in the experimental environment. Standard theory predicts no WTA/WTP gap under symmetric information and a large WTA/WTP gap under asymmetric information.[2] In contrast, ALA predicts similarly sized gaps under symmetric and asymmetric information and adaptive behavior. The effect of the posited simplified beliefs and different levels of loss aversion on bidding is shown using static analysis. The experimental results are presented in Section 5. The effects of the endowment, asymmetric information, and trading experience are analyzed. The results provide some support for the predictions of ALA. Bidders do not respond optimally to asymmetric information. Under symmetric information, there is a WTA/WTP gap. Under asymmetric information, there is a WTA/WTP gap that is smaller than predicted by standard theory. There is some evidence of subjects adjusting their behavior as they gain experience.

In Section 6 a structural version of ALA is applied to the experimental data. There is now

[2] That standard theory can predict a WTA/WTP gap is not unique to the experimental environment. For example, Glosten and Milgrom (1985) show how asymmetric information can lead to a bid/ask spread.

an emerging literature on estimating structural versions of behavioral game theory models (see for example Camerer, Nunnari and Palfrey (2016) and Turocy and Cason (2015)). This paper is the first, to the best of my knowledge, to estimate a structural model of the process by which the WTA/WTP gap adjusts. The parameter estimates suggest that subjects are loss averse and that loss aversion is adjusted as the theory predicts. ALA is compared to several alternative models, including variants of quantal response equilibrium, analogy-based expectation equilibrium, cursed equilibrium, level-k thinking and experience-weighted attraction. The models are also applied to data from previous experiments on common value auctions and the acquiring a company task.

Finally, Section 7 concludes. ALA and the experiment are discussed as well as some of the broader issues involved in modeling changing behavior.

1 Related literature

This section describes how ALA fits with the literature on the endowment effect and experience and the literature on behavioral game theory. ALA is compared and contrasted with other theories.

1.1 The endowment effect, uncertainty and market experience

The endowment effect (a WTA/WTP gap or a reluctance to exchange an endowed item for an alternative) has been replicated in many experiments.[3] Table 1 lists a number of studies that elicited WTA/WTP in repeated laboratory markets. In the majority of cases, the WTA/WTP gap decays. There are, however, exceptions. It seems both the mechanism used to elicit values and the type of item being valued matter. A range of theories has been presented in the literature attempting to explain the endowment effect and when it occurs. The theories involve uncertainty about the risks of trading (Engelmann and Hollard, 2010), uncertainty about the price and aversion to bad deals (Isoni, 2011), taste uncertainty (Loomes, Orr and Sugden, 2009), bounded rationality and heuristics (Bateman et al., 2005; Braga and Starmer, 2005), the discovery of preferences and shaping of preferences (Loomes, Starmer and Sugden, 2003), and whether people are intending to trade (Novemsky and Kahneman, 2005; Koszegi and Rabin, 2006).[4]

[3]There is some debate over the status of the endowment effect. Plott and Zeiler (2005) suggest that the WTA/WTP gap reported in many studies is caused by subjects' misconceptions. They ran an experiment with controls for misconceptions and found that, when a full set of controls is used, there is not a WTA/WTP gap for mugs. Isoni, Loomes and Sugden (2011) call into question Plott and Zeiler's interpretation. They also replicate Plott and Zeiler's results using mugs but find the same set of controls does not eliminate the WTA/WTP gap for lotteries. The reason for the different results with mugs and lotteries is not well understood. The current paper investigates the WTA/WTP gap for lotteries.

[4]Another possible explanation of the endowment effect is evolution. Heifetz and Segev (2004) argue the WTA/WTP gap is an example of toughness and that a toughness bias may be evolutionary viable. They show how in an evolutionary model toughness can emerge in bargaining with asymmetric information. Furthermore, Chen, Lakshminarayanan and Santos (2006) ran experiments using capuchin monkeys and find evidence of loss aversion, which suggests it may have an evolutionary origin. More recently, in a paper first distributed after an earlier version of this paper, Frenkel, Heller and Teper (2018) have explored whether a combination of the endowment effect and susceptibility to the winner's curse could be evolutionarily stable. It is not clear, however, how these evolutionary accounts could explain the effects of experience on the endowment effect.

Table 1: The WTA/WTP gap and the effects of laboratory market experience

Study	Good(s)	Trials	Main finding
Coursey, Hovis and Schulze 1987	tasting a bitter liquid	5-10	Gap reduces
Kahneman, Knetsch and Thaler 1990	induced value tokens	1-3	No gap
	pens, mugs, binoculars	4-5	Gap persists
Shogren et al. 1994	chocolate and coffee mugs	5	Gap closes
	food safety	20	Gap persists
List and Shogren 1999	chocolate bars	4	Gap closes
	food safety	9-10	Gap reduces
Shogren et al. 2001	chocolate and mugs (2nd price auction)	10	Gap closes
	chocolate and mugs (random price auction)	10	Gap closes
Knetsch, Tang and Thaler 2001	coffee mugs (2nd price auction)	6	Gap closes
	coffee mugs (9th price auction)	6	Gap widens
Loomes, Starmer and Sugden 2003	2 unresolved risky lotteries	6	Gap closes

The table summarizes the results of studies of the WTA/WTP gap in repeated markets. It does not include studies in which WTA and WTP valuations were elicited in individual decision-making tasks, studies in which markets were not repeated, or studies using an exchange of goods without money.

Uncertainty related to trading has been used to explain the endowment effect and the effects of experience. Engelmann and Hollard (2010) investigate how market experience affects the endowment effect in exchange of goods experiments. While not presenting an explicit model, they conjecture that trade uncertainty (costs and risks associated with trading) is the main cause of the endowment effect. On this view, people who overestimate the risks of trading will tend not to trade, and, hence, not learn that trading is less risky than they feared. They reported an exchange of goods experiment with two stages. In one treatment, subjects were forced to trade their endowment in the first stage whereas, in another, they were not. In the second stage, trading was voluntary in both treatments. The results show that subjects who were forced to trade in the first stage traded more in the second stage. ALA makes broadly similar predictions. People only adjust their loss aversion after trading, so, in a setting in which highly loss averse people estimate that all trades will not be profitable, such people will not trade and, hence, not become less loss averse.

In repeated auction experiments, the price produced by the auction is not known when subjects place their bids. Isoni (2011) presents a simple model that explains some features of previously reported experimental results. In the model, utility has two components: (a) reference independent utility for money and goods and (b) good/bad deal utility. Before the auction results are known, a person forms an expectation of the price. If they buy below the expected price, there is positive good deal utility; if they buy above the expected price, there is negative bad deal utility. Potential bad deals are given more weight. This results in a WTA/WTP gap. When the auctions are repeated, uncertainty about the price decreases, which results in the WTA/WTP gap decreasing. The model also predicts bids will be adjusted towards previously observed prices (shaping). ALA makes similar predictions, but they are driven by different mechanisms. The decay of the WTA/WTP gap is caused by loss aversion decreasing.

Another way uncertainty could explain the endowment effect is when holding a position will deliver different levels of utility in different states of nature. Loomes, Orr and Sugden (2009) develop a model in which such uncertainty coupled with asymmetric attitudes to losses and gains in utility, leads to an endowment effect. The model predicts that the greater the uncertainty about the utility an item will deliver, the larger the WTA/WTP gap for the item. In the model, if market experience is associated with a decrease in uncertainty about the items traded, market experience would decrease the WTA/WTP gap.[5] Differences in uncertainty could explain some of the differences in the results listed in Table 1. For example, there is no uncertainty about the value of induced value tokens and hence no WTA/WTP gap. At the other extreme, there is plausibly considerable uncertainty about the benefits of food safety measures, hence a WTA/WTP gap persists. In ALA, uncertainty plays an equivalent role If there is no uncertainty, there is no WTA/WTP gap. A key difference between the theories is that ALA allows experience to alter behavior even when there is no change in uncertainty.

Bateman et al. (2005) and Braga and Starmer (2005) have suggested heuristics as an explanation of the WTA/WTP gap.[6] The conjecture is that, when faced with incentive-compatible, value elicitation tasks in experiments, subjects do not report their true valuations. Instead, they use a "tactical heuristic" or "caution heuristic." The heuristic involves overstating incoming valuations (in which the subject specifies the quantity of money or a good that the subject will receive) and understating outgoing valuations (in which the subject specifies the quantity of money or a good that the subject will give up). There are two types of setting in which, assuming bounded rationality, using such a heuristic would be beneficial. First, in bargaining problems of the type studied by Myerson and Satterthwaite (1983) in which a buyer and a seller have private values for an item. In such settings, a buyer can achieve a higher payoff by understating his/her value for the item. Second, in an uncertain common values setting, such as bidding for a jar of coins, or an asymmetric information setting, such as buying a used car. Here, the item's expected value conditional on buying is less than its unconditional expected value, so offering to trade at the unconditional expected value is a mistake. In the private values setting, it is not clear why market experience would alter the use of the heuristic. Experienced and inexperienced traders alike have a reason not to reveal their true preferences. On the other hand, in the common values setting, if market experience is associated with a reduction in the uncertainty about the item's value, more experienced traders would have less reason to be cautious when trading. This is consistent with List's (2003; 2004) findings that people with more experience trading in naturally occurring markets are less prone to exhibit the endowment effect in simple exchange and valuation decision problems. It is this common value version of the caution

[5] In Loomes, Orr and Sugden's model, it is not only market experience that can reduce uncertainty. See Humphrey, Lindsay and Starmer (2017) for an experimental investigation of how non-market experiences influence the endowment effect.

[6] A related heuristics-based hypothesis is suggested by Ert and Erev (2008). They posit that people use a "lemon avoidance heuristic" when deciding whether to accept a gamble. They found that subjects were more likely to reject a gamble when they were approached in the hallway than when they were offered the same gamble in the lab. ALA models loss aversion as just depending on experience, however, it is natural to think of a richer model in which the loss aversion exhibited depends on experience and environmental factors.

heuristic that motivates ALA.

Loomes, Starmer and Sugden (2003) investigate the effect of market experience on anomalies with a focus on the WTA/WTP gap. They consider two broad hypotheses. First, the discovered preference hypothesis, that, in repeated markets, traders learn to act on "true" preferences that are consistent with standard theory. The adjustment mechanism could be *refining*, that markets have a general tendency to induce traders to make decisions that increasingly reflect their true preferences. It could also be *market discipline*, that agents adjust their behavior only after making errors that are ex-post costly. ALA shares features with the market discipline hypothesis. In ALA, agents do have underlying preferences, but decisions do not always reflect these preferences. There are also important differences. In ALA, loss aversion is only updated after trading and is updated whether or not there was a costly error. Under the market discipline hypothesis, behavior is only changed if there was a costly error, and it can change whether or not the agent traded. Another difference is that, under the market discipline hypothesis, when behavior is adjusted, it is adjusted in the direction of the optimal behavior whereas, under ALA, this is not necessarily the case. For example, in ALA, if an agent buys a lottery for less than its certainty equivalent in a Vickrey auction but it pays out zero, they will tend to bid less for it in the future whereas the optimal behavior is to bid more. Second, the hypothesis that market experience alters or shapes preferences. Loomes et al. suggest the following mechanism "in repeated auctions in which prices have no information content, there is a tendency for agents to adjust their bids towards the price observed in the previous market period." A version of shaping could explain Knetsch, Tang and Thaler's 9th price auction results listed in Table 1. The auctions had 10 bidders and in the buying version, the 9th highest bid was the price and in the selling version, the 9th lowest ask was the price. Hence in both auctions, the price is set by one of the traders who is least willing to trade. If bidders adjust their bid towards the observed price, the WTA/WTP gap will tend to widen.

Finally, Novemsky and Kahneman (2005) explore the conjecture that, when goods are given up "as intended," there is no loss aversion. The idea is that loss aversion plays no role in routine transactions. One way to model this is by using Koszegi and Rabin's (2006) framework. They assume agents are loss averse but model the reference point as an agent's recently held rational expectation about outcomes rather than their current holdings. This approach seems to explain behavior in some contexts. It is not clear how such an explanation would work in repeated markets using the Vickrey mechanism where it is known in advance that a fixed number of participants will trade. In ALA, in contrast, not trading is always taken as the reference point, and the decay of the endowment effect is due to traders becoming less loss averse.

1.2 Behavioral game theory

There are a number of behavioral game theory models that are related to ALA. ALA is principally a model of dynamics rather than equilibrium behavior. It shares some features with simple reinforcement-learning models, such as those studied by Erev and Roth (1998). In reinforcement learning, pure strategies in a game have associated propensities that determine the probability that each strategy will be played. When a given strategy is played and is successful, its propensity and, hence, the probability of it being played again, is increased. In ALA, an agent has a degree of loss aversion that influences his/her anticipated gains from trades involving risk and, hence, willingness to trade. When a trade is made and the payoff is better than anticipated, he/she becomes less loss averse and more willing to trade. There are, however, important differences between the theories. In reinforcement learning, initial propensities are arbitrary, and agents have no understanding of the game's structure. In ALA, the agent's estimate depends on the structure of the game. For instance, a bid for a lottery in a Vickrey auction depends on the odds and prizes of the lottery. In reinforcement learning, *propensities to play strategies* in repeated games are adjusted in response to experienced outcomes. In ALA, *loss aversion* is adjusted, which can determine behavior across different games. That is, the effect of experience of playing one game can carry over to other types of games.

ALA can also be compared to Camerer and Ho's (1999) experience-weighted attraction (EWA). EWA is similar to reinforcement learning. The key difference is that strategies that were not played get reinforced using hypothetical payoffs, with a parameter determining the relative weight they receive. EWA includes reinforcement learning and belief learning as special cases. ALA differs from EWA in that loss aversion is not updated based on hypothetical payoffs.[7] This approach lets ALA be applied in settings in which the payoffs from unplayed actions are not readily available. In EWA, like reinforcement learning, the effects of experience do not carry over to other types of game whereas in ALA they do.

There are several ways beliefs about other's behavior can be modeled. In level-k and cognitive hierarchy models (Nagel, 1995; Stahl and Wilson, 1994, 1995), players have different levels. Some assumption is made about how level zero players behave, such as that they play all actions with equal probability, then a level k player, where $k > 0$, believes other players are level $k-1$ players and best responds to these beliefs. An alternative approach to modeling beliefs is used in analogy-based expectation equilibrium (ABEE) (Jehiel, 2005; Jehiel and Koessler, 2008). In such models, players have correct beliefs about the average behavior of others across information sets. Eyster and Rabin's (2005) cursed equilibrium (CE) is a similar model. In CE, a parameter $\chi \in [0,1]$ measures cursedness, the degree to which agents do not account for others having different information. Level-k models, ABEE and CE are static models without correct beliefs. Consequently, players will experience outcomes inconsistent with their beliefs. In ALA, in contrast, players are loss averse and loss aversion is adjusted. This allows players to reconcile differences between anticipated payoffs and realized payoffs.

ALA has some similar features to the concept of *behavioral equilibrium (BE)* introduced by Esponda (2008). In a BE, naive players have correct beliefs about the equilibrium distributions of observable actions and observable states of nature but do not realize that extra information can be obtained by considering the joint distribution of actions and states. Although ALA is not an

[7] It would be possible to extend ALA to incorporate updating loss aversion based on hypothetical payoffs, however, it would make the model more complex since beliefs about payoffs from unplayed strategies would need to be specified.

equilibrium model, it has a similar property to behavioral equilibrium in that the uninformed can adjust their behavior so they do not repeatedly fall prey to the winner's curse.

Compte and Postlewaite (2012) consider settings where agents do not know the joint distribution over states of nature and the signals they receive. Agents pick a decision rule from a limited set that on average produces good outcomes. Compte and Postlewaite argue that the ruled picked will often involve cautious behavior in the sense of choosing alternatives that are easier to evaluate, e.g. avoiding ambiguity or sticking with the status quo. ALA could be considered a model of how such a rule, the level of loss aversion, is determined. Note that in ALA it is assumed the updating of loss aversion is an automatic rather than a deliberate process.

ALA also shares features with *impulse balance theory* (IBT) (Selten, Abbink and Cox, 2005). Like IBT, in ALA, there is a single variable that is adjusted (loss aversion in ALA). The theories differ in that IBT is a theory about the end point of a learning process whereas ALA is a theory about the learning process. Another important distinction is that, in ALA, it is differences between obtained and anticipated payoffs that lead to changes in behavior, whereas, in IBT, the obtained payoff is compared to hypothetical payoffs from other actions.

2 Adaptive loss aversion

Adaptive loss aversion is a behavioral model with three components. First, beliefs are based on a simplified model of others' behavior. Second, decisions are determined by anticipated utility, which is composed of outcome utility and gain-loss utility. Gain-loss utility is reference-dependent with pure strategies defining the reference point and current loss aversion, denoted λ_{it}, determining the extra weight applied to losses. Third, after playing an action and receiving feedback, if the level of utility realized was not anticipated the degree of loss aversion, λ_{it}, is updated. This section defines the primitives of the model and the notation used to describe them.

Let Ω denote the set of states of nature. Consider a sequential game with a set of players N that are indexed $1,\dots,n$. A pure strategy for player i is defined $s_i : H_i \mapsto A_i$ where H_i is i's information sets and A_i is i's actions. A profile of pure strategies for each of the players is denoted $s = \langle s_1,\dots,s_n\rangle$ and the set of all possible profiles is denoted S. Outcome utility depends on the state of nature and profile of strategies. Each player has an outcome utility function $u_i : \Omega \times S \mapsto \Re$. In this paper, it will be assumed outcome utility is simply the amount of money held. Each player has beliefs $\mu_i : \Omega \times S_{-i} \mapsto [0,1]$ consisting of beliefs about the state of nature $\mu_{i\Omega} : \Omega \mapsto [0,1]$ and beliefs about each of the other player's strategies $\mu_{ij} : S_j \mapsto [0,1]$ where $i \neq j$. Player i believes the strategies of other players are independent of each other and the state of nature, hence $\mu_i(\omega, s_{-i}) = \mu_{i\Omega}(\omega)\prod_{j\in N\setminus i}\mu_{ij}(s_j)$ where $\omega \in \Omega$ is a state of nature and $s_{-i} \in S_{-i}$ is a profile of pure strategies of the other players. It is important to note that even when strategies are independent of each other and the state of nature, actions can be correlated since a strategy can involve playing different actions at different information sets. Assume players have correct beliefs about the probability of different states of nature occurring $\mu_{i\Omega}$ but do not necessarily have correct beliefs about the probability of other players playing different strategies. There are various forms the model of beliefs could take. ALA has some flexibility in that different models can be "plugged in." For simplicity, this paper will mostly consider the model where player i believes every other player j follows the mixed strategy that consists of playing all available actions with equal probability at every information set.

Anticipated utility is reference-dependent. The reference-points are defined using pure strategies.[8] To simplify the notation, expectations such as $\Sigma_{\omega\in\Omega}\Sigma_{s_{-i}\in S_{-i}}\mu_i(\omega,s)u_i(\omega,s_i,s_{-i})$ are denoted as $E_{\mu_i}[u_i(\omega,s_i,s_{-i})]$. The anticipated utility of strategy $s_i \in S_i$ from reference point $r \in S_i$ with beliefs μ_i is the sum of the expected outcome utility from s_i and the expected gain-loss utility. The gain-loss utility captures the effect of the reference point.

$$AU_i(s_i|r,\mu_i) = E_{\mu_i}\Big[\underbrace{u_i(\omega,s_i,s_{-i})}_{\text{outcome utility}}\Big] + E_{\mu_i}\Big[\underbrace{\psi\left(u_i(\omega,s_i,s_{-i}) - u_i(\omega,r,s_{-i})\right)}_{\text{gain-loss utility}}\Big] \tag{1}$$

Gain-loss utility for state ω and opponents' strategies s_{-i} is $\psi(x)$ where x is the difference between the utility delivered by the reference point r and strategy s_i. The function ψ maps changes in utility x to gain-loss utility by weighting losses using the agent's current loss aversion $\lambda_{it} > 0$.

$$\psi(x) = \begin{cases} x(\lambda_{it} - 1) & \text{if } x < 0, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

When $\lambda > 1$, the agent is loss averse and anticipated utility depends on the reference point. When $\lambda = 1$, the gain-loss utility is zero so anticipated utility is independent of the reference point.

A natural choice for the reference point r is a strategy that will result in no trade. In a setting with posted prices, r could simply be rejecting the offered price. In an experimental auction where entering some bid is required, r could be bidding zero in a buying auction (or asking the maximum permissible amount in a selling auction).

Given the reference point, the agent picks a strategy that maximizes anticipated utility.

$$s_i^* \in \arg\max_{s_i} AU_i(s_i|r,\mu_i) \tag{3}$$

Notice that when players have correct beliefs and $\lambda = 1$, Equation 3 gives a best response and if all players play such responses, the outcome is a standard Bayesian Nash equilibrium.

In ALA, changes in λ are caused by differences between the anticipated utility before playing some action and the utility after updating their reference point and receiving feedback. It is assumed that the updating of λ happens automatically rather than as the result of a deliberate choice by the agent. The formulation below can be applied to games generally. Let $t = 1, 2, \ldots$ denote the period.

[8] A similar approach is taken by Sugden (2003) who defines reference-dependent preferences using Savage's framework of states, consequences, and acts. A key difference is that this paper defines reference-dependent preferences using strategies, outcomes and payoffs. This makes the model readily applicable to games as well as individual decision-making problems.

Agent i plays strategy s_i^t and receives some feedback. Agent i updates their belief about strategies and the state of nature in this period to μ_i^t. The agent's weighted unanticipated utility, denoted z_{it}, is calculated as shown below. A weighting parameter $w \geq 0$ measures how sensitive the agent is to unanticipated outcomes.

$$z_{it} = w\Big[\underbrace{AU_i\left(s_i^t|s_i^t,\mu_i^t\right)}_{\text{after}} - \underbrace{AU_i\left(s_i^t|r,\mu_i\right)}_{\text{before}}\Big] \tag{4}$$

This paper will focus on the case where feedback includes all payoff relevant information.[9] In this case, after receiving feedback an agent will update their beliefs to $\mu_i^t(\omega^t, s_{-i}^t) = 0$ for all outcomes that are inconsistent with the feedback. Hence, the anticipated utility after trading $AU_i\left(s_i^t|s_i^t,\mu_i^t\right)$ simplifies to $u_i(\omega^t, s_i^t, s_{-i}^t)$ where s_{-i}^t is the profile of strategies played by the other players and ω^t is the state of nature.

In an auction or market, a possible refinement is calculating the anticipated utility conditional on the realized price. It is plausible traders would respond differently to getting a worse than expected payoff due to the price being high and getting one due to a bad state of nature occurring. Conditioning the anticipated utility on the price isolates the effect of the realized state of nature from the effect of the realized price.

At time t the degree of loss aversion λ_t is a decreasing function of the sum of unanticipated utility $\sum_{j=0}^{t-1} z_{ij}$ where z_{i0} is a parameter that determines loss aversion in period 1.

$$\lambda_{it} = e^{-\sum_{j=0}^{t-1} z_{ij}} \tag{5}$$

It follows that $\lambda_{it+1} = \exp\left(\log(\lambda_{it}) - z_{it}\right)$. When the outcomes from trading have, on average, been worse than anticipated, loss aversion λ is greater than one. Following a trade, if the outcome is better than anticipated, then λ decreases which increases anticipated utility in the next period. If the outcome is worse than anticipated, then the converse occurs. If the outcome is as anticipated, then loss aversion does not change.

The properties of ALA described above have several implications. The evolution of λ depends on whether the outcomes of trading are better or worse than anticipated. When beliefs are correct and $\lambda = 1$, the outcomes of trading will on average be as anticipated. This is because with $\lambda = 1$ gain-loss utility is zero and with correct beliefs, $\mu_i(\omega, s_{-i})$ equals the true probability of the outcome occurring. Systematic differences between anticipated and obtained payoffs can result from loss aversion or incorrect beliefs. When beliefs are correct and $\lambda > 1$, the outcomes of trading will tend on average to be better than anticipated. This is because gain-loss utility will be negative when calculating anticipated utility but zero when assessing the outcomes of trading. When beliefs are incorrect and $\lambda = 1$, the outcomes of trading can on average be better or worse than anticipated depending on whether the incorrect beliefs overweight the good or bad outcomes. Consider a lemons

[9]The model can also be applied to cases where agents receive feedback that only resolves some of the uncertainty, such as auctions for unresolved lotteries or for goods with unknown quality.

type asymmetric information setting where the seller knows the state of nature but the buyer does not. Suppose the seller tends to sell in bad states of nature but not in good ones. The buyer does not realize the probability of a good state conditional on buying is less than the unconditional probability of a good state. The outcomes from trading will tend to be worse than anticipated for the buyer. Accordingly, market experience in settings with symmetric and asymmetric information can have different effects on λ.

3 Experimental design

This section describes the experimental design and how the experiment was implemented. The predictions of standard theory and ALA are discussed in the next section. The environment was chosen to capture key features of buying and selling under symmetric and asymmetric information. Following Loomes, Starmer and Sugden (2003), median-price Vickrey auctions for lotteries were used. Groups had an odd number of members. There were two types of auctions: buying and selling. In a buying auction, each member of the group is endowed with cash and bids to buy one lottery from the experimenter. The price, p, is the median bid. Everyone who bid above p pays p and receives one lottery. In a selling auction, each member of the group is endowed with one lottery and submits an ask to sell it to the experimenter. The price, p, is the median ask. Everyone who asked below p receives p and gives up the lottery.

A novel feature of the design is that auctions occurred under symmetric and asymmetric information. Let the auctioned lottery be denoted ℓ and have expected value $E[\ell]$. Under symmetric information, everyone had the same information about the state of nature when they were placing their bids. Under asymmetric information, a minority of the members of each trading group knew whether it was a high or low state of nature, $E[\ell|state = high] > E[\ell|state = low]$, before they placed their bids. Suppose all the informed bid b_I and all uninformed bid b_U and $b_I \neq b_U$. The median bid is the price and the majority of bids are placed by the uninformed so the price will be b_U.[10]

In the experiment, the following lotteries were used. A *low state lottery* with an expected value of 11.5 that offered a 0.37 chance of 31 credits and zero otherwise. A *high state lottery* with an expected value of 83.3 that offered a 0.6 chance of 97 credits and 63 otherwise. A composite lottery with an expected value of 52.4 that offered a 0.16 chance of 31 credits, a 0.23 chance of 63 credits, a 0.34 chance of 97 credits, and zero otherwise. The composite lottery is constructed by combining the low state and high state lotteries.[11]

[10] If the price were determined by the informed, then the price under asymmetric information would be no different to what it would be if everyone were informed. In Akerlof's (1970) market for lemons model and the acquiring a company task described in the introduction, asymmetric information could lead to the market unraveling and no trade occurring. In the experiment, this was not possible. An important feature of the design was that subjects were trading with the experimenter, and the experimenter was always willing to trade at the price produced by the auction.

[11] We can think of the composite lottery as a lottery with two outcomes that are themselves lotteries. With probability 0.43, the outcome of the composite lottery is the low state lottery; with probability 0.57, it is the high state lottery. The low state lottery pays out 31 with probability 0.37, so the composite lottery will pay out 31 with probability $0.37 \times 0.43 \approx 0.16$. The probability values for the other payouts are calculated in the same way.

Table 2: The treatments

Treatment	Regime		Type	Subjects	Trading
	Rounds 1-10	Rounds 11-20			groups
SS	Symmetric	Symmetric	Buying	22	4
			Selling	29	5
SA	Symmetric	Asymmetric	Buying	22	4
			Selling	31	5
AS	Asymmetric	Symmetric	Buying	27	5
			Selling	31	5
AA	Asymmetric	Asymmetric	Buying	24	4
			Selling	22	4

Each row of the table represents a treatment. Each trading group consisted of five or seven subjects.

Each subject was assigned to a trading group. Members of a trading group bid against each other in a series of 20 auction rounds. After each auction, the lotteries were played out and subjects told how much they had made or lost in the round. Each trading group and, hence, each subject was assigned to one of eight treatments. The organization of the treatments is shown in Table 2. The experiment was divided into two parts, each consisting of 10 rounds. Some treatments switched between symmetric and asymmetric information after ten rounds while others did not. In the rest of this paper, the abbreviations SS, SA, AS, and AA shown in the first column of the table are used to refer to the treatments.

A total of 208 subjects participated in the experiment.[12] Subjects were divided into trading groups of five or seven that traded in the same auctions. In the buying treatments, subjects were endowed with *credits* and bid to buy a lottery (the credits were exchanged for cash at the end of the experiment). Subjects completed the sentence “I am willing to buy the lottery from the experimenter if the price is less than __ credits” by typing a value. In the selling treatments, they were endowed with a lottery and submitted asks to sell it. Subjects completed, “I am willing to sell the lottery to the experimenter if the price is more than __ credits.” When all subjects had entered values, the computer selected the median as the market price.

In rounds with symmetric information, the composite lottery was traded. In rounds with asymmetric information, the minority were informed (two in trading groups of five, three in trading groups of seven). The informed traders were told whether it was a high or low state before bidding; the uninformed traders were not. So, effectively, the informed were trading either the high or low state lotteries, while the uninformed were trading the composite lottery. The uninformed were told that there were informed subjects in the trading group and told what the informed would have been told.

Figure 1 shows how the lotteries were presented to the subjects when they were prompted to place bids (complete screenshots of the experimental software are included in a supplementary file).

[12]The experiment was conducted at the University of Nottingham. Subjects were recruited using ORSEE (Greiner, 2015). The experimental software was programmed using Java.

Figure 1: Presentation of lotteries

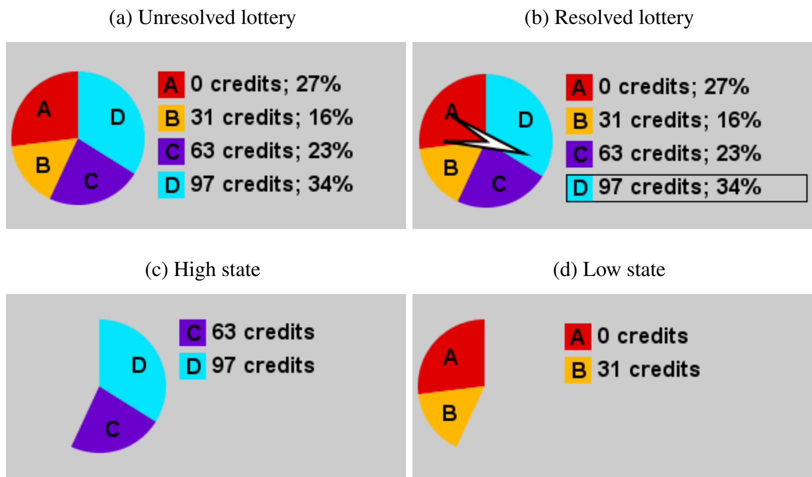
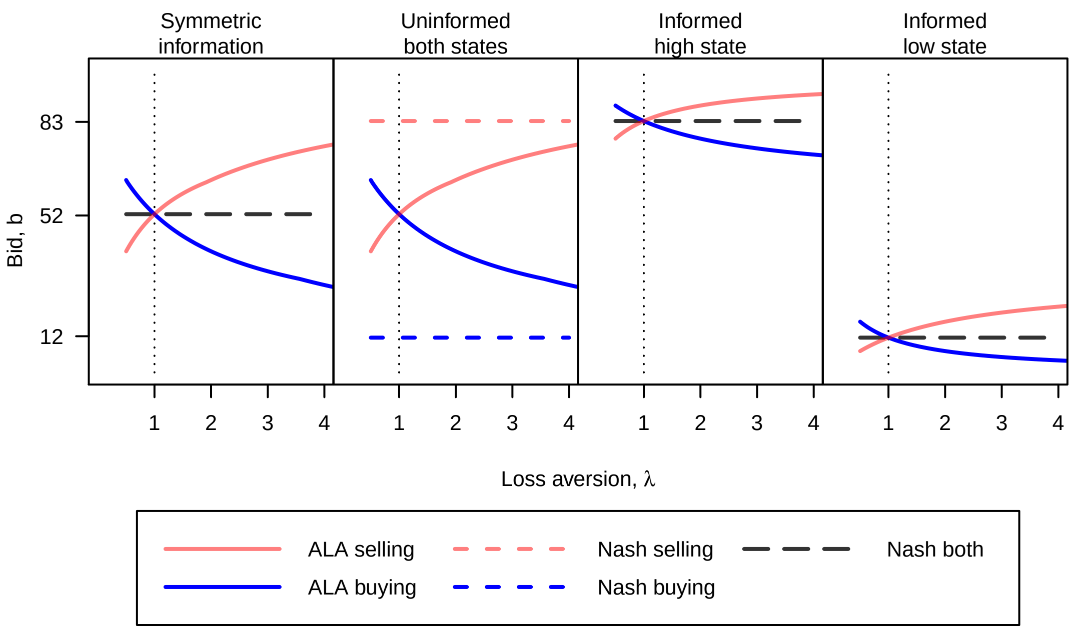


Figure 1a was shown to everyone. In rounds with asymmetric information, the informed were also shown Figure 1c or Figure 1d so that they knew before bidding whether it was a high or low state. The lottery outcomes were determined by computer-generated random numbers. There was one lottery outcome per trading group per round. The outcomes were revealed to subjects after the outcome of each auction. An animated spinning arrow, Figure 1b, was used to present the lottery outcomes.

A paper copy of the instructions was given to the subjects (included in a supplementary file). Before the experiment started, the experimenter read the instructions aloud and then gave subjects the opportunity to ask questions. There were just two versions of the instructions. One version covered the four buying treatments; the other covered the four selling treatments. All subjects were told about symmetric and asymmetric information even if they did not participate in auctions under both regimes. The motivation for this was to isolate the effect of knowing about asymmetric information from actually experiencing it. A subject, for example, in round 9 of the SS buying treatment had no way of knowing whether he/she was in the SS or SA treatment. Approximately 20 subjects participated in each session and were randomly assigned to groups. Within a session, all groups were assigned to buying treatments or all were assigned to selling treatments. However, not all groups were assigned to the same treatment. For instance, a single session with four groups could have groups assigned to each of the SS, SA, AS, and AA treatments. These features were intended to minimize treatment effects other than differences in the information structure and to allow results from the different treatments to be pooled in the analysis. Each session lasted between 40 and 60 minutes. The average payment was £8.17.

Figure 2: ALA comparative statics



4 Predictions

The details of the market mechanism and the lottery can be used to produce predictions for standard theory and ALA.

When bidders are risk-neutral expected utility maximizers, there is a Nash equilibrium in which WTA equals WTP under symmetric information.[13] Suppose there are three bidders to buy the lottery ℓ in a median price auction. It is readily verified that for all three bidders, it is a weakly dominant strategy to bid $E[\ell]$, the expected value of the item. The same is true for a selling auction. Under asymmetric information, in contrast, there is an equilibrium in which WTA exceeds WTP. Suppose that one of the bidders is told if it is a high or low state. It is a weakly dominant strategy for the informed to bid $E[\ell|state = low]$ in the low state and $E[\ell|state = high]$ in the high state. The other two bidders, the uninformed, know the informed will observe the state of nature before bidding but cannot observe it themselves. There are no weakly dominant strategies for the uninformed.[14]

[13]Risk-neutrality is assumed because the stakes in the experiment are relatively modest. If agents maximize the expected utility of wealth and do not exhibit extreme risk aversion over high stakes, Rabin's (2000) calibration theorem suggests they should be approximately risk-neutral over modest stakes. If income and wealth enter separately into agents' utility functions, then the resultant model can predict behavior, such as a WTA/WTP gap and preference reversals, that is typically thought of as inconsistent with standard theory (Lindsay, 2013).

[14]Let $\tilde{b}$ satisfy $E[\ell|state = low] < \tilde{b} < E[\ell]$. If the informed player bids $\tilde{b}$ in both states and the first uninformed player also bids $\tilde{b}$, the best response for the second uninformed player is to bid $b > \tilde{b}$, whereas if the informed bids $\underline{b} = E[\ell|state = low]$ in the low state and $\bar{b} = E[\ell|state = high]$ in the high state and the first uninformed player bids $\tilde{b}$, the best response for the second uninformed player is to bid $b < \tilde{b}$. Hence, there is no weakly dominant strategy for the uninformed.

However, how they bid can be predicted using iterative deletion of weakly dominated strategies.[15] For the informed, bidding $E[\ell|state = low]$ in the low state and $E[\ell|state = high]$ in the high state weakly dominates all other strategies, so all other strategies can be removed. In the resulting game, it is a weakly dominant strategy for the uninformed to bid $E[\ell|state = low]$. Conversely, in a median price selling auction, after the informed's weakly dominated strategies are deleted, it is a weakly dominant strategy for the uninformed to ask $E[\ell|state = high]$. So the uninformed have a reason to bid lower in buying auctions than they ask in selling auctions.

Under ALA, the bid that gives the highest anticipated utility can be found using Equation 3 from Section 2. The optimal bid will depend on the value of λ. Figure 2 shows comparative statics. The solid lines are the predictions of ALA with different levels of loss aversion λ. The reference point is not trading (bidding zero when buying or asking the maximum allowed amount when selling). The dashed lines are the risk-neutral Nash equilibrium bids obtained by the iterative deletion of weakly dominated strategies. For ALA, when $\lambda < 1$, $WTP > WTA$; when $\lambda = 1$, $WTP = WTA$; and when $\lambda > 1$, $WTP < WTA$. The WTA/WTA gap widens as λ increases above one. Under symmetric information and for the informed under asymmetric information, the Nash and ALA predictions coincide when $\lambda = 1$. For the uninformed under asymmetric information, as λ increases above one, WTP and WTA approach their respective Nash values.

The intuition of dynamics under ALA is as follows. Agents perceive settings with symmetric and asymmetric information as equivalent and adjust λ when trading produces better or worse than anticipated outcomes. Suppose subjects enter the laboratory with loss aversion $\lambda = 2$. Under symmetric information, they will bid below the expected value of the lottery and ask above it. When they trade, on average, the outcomes of trading will be better than anticipated, so λ will be adjusted downwards towards one. Under asymmetric information, the uninformed will bid above the Nash buying value and ask below the Nash value. When they trade, on average the outcomes of trading will be worse than anticipated, so λ will be adjusted upwards, and bids will adjust towards their respective Nash values (WTA reaches its Nash value when $\lambda = 7.6$ and WTP reaches it when $\lambda = 14.1$).

The testable predictions of ALA can be summarized as follows.

1. The uninformed subjects will not take account of the informed's extra information.

2. If subjects at the start of the experiment are loss averse, then there will be a WTA/WTP gap. Under symmetric information, subjects will underestimate the payoffs from trading, so realized outcomes from trading will, on average, be better than anticipated. If subjects become less loss averse in response, then the size of the WTA/WTP gap will tend to decrease. Conversely, under asymmetric information, the uninformed will tend to overestimate the payoffs from trading, so realized outcomes from trading will, on average, be worse than anticipated. The WTA/WTP gap will tend to persist or increase.

3. Subjects will change their bidding behavior when outcomes from trading are better or worse

[15] See Marx (1999) for a discussion of iterative deletion of weakly dominated strategies.

than anticipated.

As well as considering these specific predictions, the overall fit of ALA will be assessed and compared to other models using structural estimation.

5 Experimental results

The 208 subjects were divided into 36 trading groups (Table 2 shows how the subjects and trading groups were divided among the eight treatments). In each auction, every subject submitted a bid or ask. Every subject completed 20 auctions giving a total of 4,160 observations. A subject is classified as 'informed' if for at least one part of the experiment, he/she was an informed trader. A subject is classified as 'uninformed' if he/she was never an informed trader. This classification enables the within subject effect of different information structures to be compared. The evolution of bids and asks submitted by uninformed and informed subjects in each of the treatments is shown in Figure 3. Mean buying bids are generally below mean selling bids. First, consider the uninformed. There is mixed evidence of trends across rounds. In the SS treatment, there is no clear trend. On the other hand, in the AS treatment, it appears a WTA/WTP gap gradually closes after the switch to symmetric information. In the AS and SA treatments, it appears that bidding behavior gradually changes when the market switches between symmetric and asymmetric information. There are some apparent spillover effects. For example, the round 11 bidding in the AS and SA treatments is similar to round 10 bidding despite the change in information structure. The informed use their extra information, bidding higher in the high payout state. In addition, the informed exhibit a WTA/WTP gap, which is particularly apparent in the AA treatment.

The following analysis tests some of the qualitative predictions of ALA prior to the structural analysis in Section 6.

ALA predicts that people do not take into account that others may have extra information.

Result 1—Asymmetric information: Under asymmetric information, the informed exploit their extra information. The uninformed do not fully anticipate the consequences of the informed using this extra information.

Support. Table 3 shows the mean bids and asks (a) under symmetric information and (b) of the informed and uninformed under asymmetric information. It also shows the mean lottery payouts under asymmetric information conditional on whether the uninformed trade. In both buying and selling auctions, the informed bid high in the high state and low in the low state. As a consequence, in buying auctions, the informed tend to buy when it is a high state leaving the uninformed to buy in the low state. This means the expected value of the lottery conditional on an uninformed buying is less than the expected value of the lottery. The uninformed do not fully anticipate this, and, on average, bid 42.86 when the expected value of the lottery conditional on them trading is just 30.07.

Figure 3: The evolution of bids by treatment

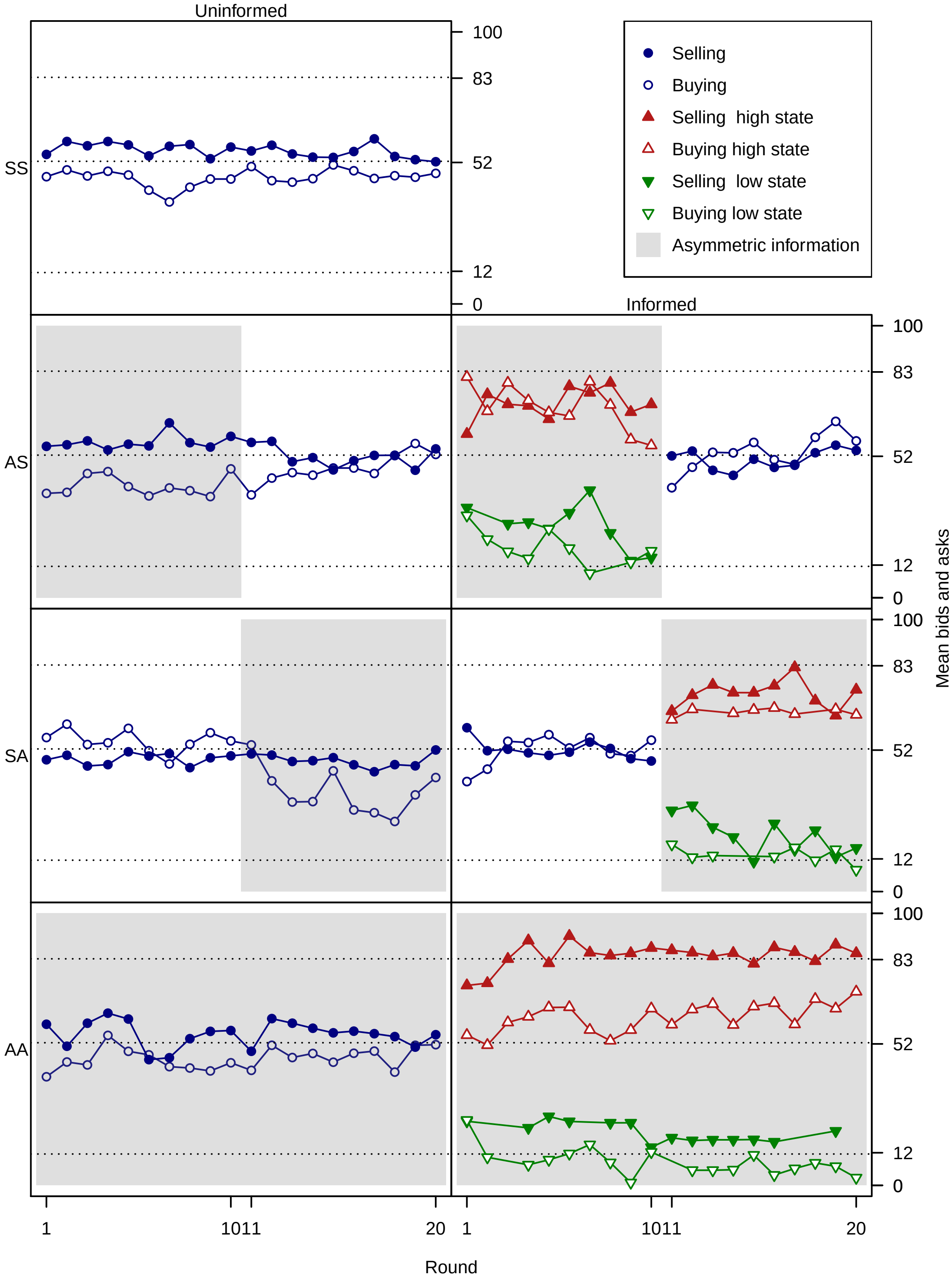


Table 3: Bidding and Lottery Payouts

		Buying	Selling
Bidding under Symmetric Information			
	Bid	49.20	53.51
		(0.58)	(0.45)
Bidding under Asymmetric Information			
Informed bids			
	High state	64.68	77.58
		(0.85)	(0.89)
	Low state	12.18	22.19
		(0.86)	(1.15)
Uninformed bids			
	Bid	42.86	53.92
		(0.86)	(0.82)
Lottery Payouts under Asymmetric Information			
	Uninformed trades	30.07	74.94
		(2.26)	(2.16)
	Uninformed does not trade	60.60	40.37
		(1.98)	(1.87)

The table shows mean bids and asks in different treatments. It also shows the mean lottery payout under asymmetric information conditional on an uninformed subject trading. Standard errors are in parentheses.

The converse occurs in selling auctions. On average, the uninformed ask 53.92 for the lottery when the expected value of the lottery conditional on them selling is actually 74.94.

Under ALA, if subjects at the start of the experiment are loss averse, then there will be a WTA/WTP gap. Furthermore, under symmetric information, subjects will underestimate the payoff from trading, so realized outcomes from trading will, on average, be better than anticipated. If subjects become less loss averse in response, then the size of the WTA/WTP gap will tend to decrease.

Result 2—WTA/WTP gap: Under symmetric information, there is some evidence of a WTA/WTP gap that closes in a repeated market. Under asymmetric information, there is a larger WTA/WTP gap and no evidence that it closes in a repeated market.

Support. The following linear random effects model is estimated

$$b_{it} = \beta_0 + \beta_1 buying_i + \beta_2 buying\,experience_{it} + \beta_3 selling\,experience_{it} + c_i + \varepsilon_{it}, \qquad (6)$$

where b_{it} is the amount bid or asked by subject i in round t. The variable $buying_i$ is one if subject i was in a buying treatment and zero otherwise. The variable $buying\,experience_{it}$ is the number of rounds prior to t where subject i was buying under the same information structure; $selling\,experience_{it}$ is the number of rounds prior to t where subject i was selling under the same

Table 4: Evolution of bids

	Symmetric information	Uninformed asymmetric information
Buying	-5.17**	-12.50***
	(1.94)	(3.01)
Buying experience	0.24**	0.10
	(0.09)	(0.15)
Selling experience	-0.16*	-0.02
	(0.08)	(0.15)
Constant	53.70***	53.64***
	(1.28)	(2.06)
Observations	2,130	1,190
Subjects	162	92

The table shows the results of estimating equation 6 using (a) bids submitted under symmetric information and (b) bids submitted by the uninformed under asymmetric information.
Significance levels: * denotes 5 percent; ** denotes 1 percent; *** denotes 0.1 percent.

information structure. Note, a given subject was either buying for the entire experiment or selling for the entire experiment. Round invariant subject-specific effects are denoted c_i , and the residual is denoted ε_{it}.

The results of estimating two variants of equation 6 are shown in Table 4. In the first column, labeled *symmetric information*, the model is estimated using the bids placed in rounds with symmetric information, pooling observations from the relevant treatments. With controls for experience, on average, bids in buying auctions are 5.17 points below those in selling auctions (the null hypothesis $\beta_1 = 0$ is rejected, $p = 0.008$). As subjects gain experience of buying under symmetric information, bids increase (the null hypothesis $\beta_2 = 0$ is rejected, $p = 0.009$). Conversely, as subjects gain experience of selling, asks decrease (the null hypothesis $\beta_3 = 0$ is rejected, $p = 0.041$). In the second column, labeled *uninformed asymmetric information*, the model is estimated using the bids placed in rounds with asymmetric information by the uninformed. The estimates imply the average bids in buying auctions are 12.5 points below those in selling auctions (the null hypothesis $\beta_1 = 0$ is rejected, $p < 0.001$). The effects of experience are smaller than under symmetric information and not statistically significant.

In ALA, changes in bidding behavior are due to changes in loss aversion. Loss aversion decreases when the outcomes of trading are better than anticipated and increases when they are worse. To explore whether this could account for the effects of trading experience, the effect of lottery outcomes after trading on subsequent bidding was studied. Since a trader's loss aversion, λ_{it}, is not observable, a proxy for the cumulative difference between the anticipated and realized outcomes of trading is used. It is based on the realized lottery payout, $x_{it'}$, and the expected value of the lottery $E(X_{it'})$ that each subject i faced in each round t'. Let T_{it} denote the set of rounds prior to t where subject i traded. A cumulative measure was constructed as $cumulative\,lottery_{it} = \sum_{t' \in T_{it}} (x_{it'} - E(X_{it'}))$.

Result 3—Lottery outcomes and bidding: Bids are higher when lottery outcomes after trading

Table 5: The effect of lottery outcomes on bidding

	Selling		Buying		Pooled
	Symmetric	Asymmetric	Symmetric	Asymmetric	
Cumulative lottery	0.0280***	0.0186*	0.0380**	0.0219*	0.0300***
	(0.0073)	(0.0086)	(0.0121)	(0.0106)	(0.0056)
Observations	1200	1060	930	970	4160
Subjects	91	84	71	73	208

The table shows the results of estimating equation 7 with different sets of bids. The constant terms and coefficients for control variables were estimated but are not shown in the table for brevity. Significance levels: * denotes 5 percent; ** denotes 1 percent; *** denotes 0.1 percent. Standard errors are in parentheses.

have been higher than expected.

Support. The following linear random effects model is estimated using several subsets of the bids

$$b_{it} = \beta_1 h_1 + \cdots + \beta_4 h_4 + \beta_5\, cumulative\, lottery_{it} + c_i + \varepsilon_{it} \tag{7}$$

where b_{it} is the amount bid or asked by subject i in round t. The information set from which subjects placed bids is captured by a series of dummy variables $h_1, \ldots, h_4$ (which includes entries for symmetric, uninformed, informed-high, informed-low). Round invariant subject-specific effects are denoted c_i , and the residual is denoted ε_{it}. The results of estimating the model using different subsets of bids are shown in Table 5. The coefficient for $cumulative\, lottery_{it}$ is positive and significantly different from zero when the model is estimated using all bids and using various subsets of bids. It is worth noting that these results cannot readily be explained by rational belief updating or income effects. The lottery outcomes in different rounds were independent so observing the payoff in one round was not informative about the payoffs in subsequent rounds. The effects are observed for both buying and selling. In selling, in rounds where the subject trades, the seller's income is unaffected by the lottery outcome.[16]

6 Structural Analysis

In this section, two structural variants of ALA are estimated. Later, in Section 6.1, they are compared to five alternative models drawn from the literature on behavioral game theory.

In the experiment, possible bids were integers between 1 and 100 inclusive. Rather than assuming agents always pick a strategy that maximizes anticipated utility, it was assumed the value bid was picked according to a logit function with parameter $\gamma \geq 0$. In all the models, the probability of

[16]Braga, Humphrey and Starmer (2009) observe a similar effect in repeated auctions to sell "P-bets" (high probability of getting a small prize) and "dollar-bets" (low probability of getting a large prize). They find evidence consistent with their loss experience hypothesis. Subjects ask less for a lottery after holding a lottery and it paying out zero; subjects ask more for a lottery after selling it and seeing it give a high payout.

a given bid being observed is as follows.

$$\Pr(b) = \frac{\exp(\gamma AU_i(b))}{\sum_{x=0}^{100}\exp(\gamma AU_i(x))} \tag{8}$$

$AU_i(x)$ is the anticipated utility from bidding x at the current information set and given the current beliefs and reference point.[17] As γ increases, the probability that a strategy is chosen that maximizes anticipated utility approaches one. The variants of ALA and alternative models differ in how the anticipated utility is calculated.

In ALA, the anticipated utility is calculated as described in Section 2. In the model, it is assumed that an agent's degree of loss aversion λ is adjusted in response to experienced losses and gains. It is natural to suppose different individuals will have had different experiences prior to the experiment and, hence, will have different values of λ upon entering the lab. To allow for heterogeneity of this type, it is assumed λ_1, a subject's loss aversion at the start of the experiment is drawn from a log-normal distribution.[18] First, a variant of ALA labeled Constant Loss Aversion (CLA) was estimated. In this model, an individual's loss aversion is constant within the experiment. The vector of parameters to estimate θ comprises the precision γ and the mean and standard deviation (s.d.) of λ_1. If λ_1 were observable in addition to the bids, the parameters could be estimated by maximizing the following likelihood function.

$$L_i(\theta) = f(\lambda_1|\theta)\prod_t \Pr(b_{it}|\lambda_1,\theta) \tag{9}$$

Unfortunately, λ_1 is not observable so it is necessary to integrate over the possible values of λ_1.

$$L_i(\theta) = \int f(\lambda_1|\theta)\prod_t \Pr(b_{it}|\lambda_1,\theta)\, d\lambda_1 \tag{10}$$

The integral was evaluated numerically. The parameters that maximized the likelihood function were then found using numerical optimization. A similar likelihood function was used to calculate the parameters of the model with adaptive loss aversion (labeled ALA). Denote subject i's loss aversion in round t as $\lambda_{it} = g(\lambda_1, w, H_{it})$, which is calculated using the history of play H_{it} and the updating rule described in Section 2. This gives the following likelihood function.

$$L_i(\theta) = \int f(\lambda_1|\theta)\prod_t \Pr(b_{it}|g(\lambda_1,\theta,H_{it}),\theta)\, d\lambda_1 \tag{11}$$

The parameter estimates for ALA and CLA are shown in the first two columns of Table 6. The

[17]The approach taken is similar to Mckelvey and Palfrey's (1998) logit-AQRE. Players are modeled as choosing an action at an information set rather than complete plans of action. The payoffs used are calculated conditional on reaching the information set. The key difference is that the payoffs in logit-AQRE are expected utilities whereas in Equation 8 the payoffs are anticipated utility calculated with loss aversion and non-equilibrium beliefs.

[18]In the experiment, there were 20 observed bids per subject, which is not enough to estimate parameters separately for each subject. If there were significantly more observations per subject, then estimating individual-level parameters might be feasible. See Lindsay (2011) for an example of this approach.

Table 6: Maximum likelihood estimates

	ALA	CLA	EWA	Level-k	CE	ABEE	QRE
precision, γ	0.398	0.397	0.287	0.410	0.232	0.210	0.200
mean of λ_1	1.915	1.890					
standard deviation of λ_1	2.228	2.132					
adjustment, w	0.000547						
level 0				0.167			
level 1				0.702			
level 2				0.131			
cursedness, χ					0.841		
weight initial-attraction, $N(0)$			11.673				
attraction depreciation rate, ϕ			0.885				
experience depreciation rate, ρ			0.947				
weight forgone, δ			0.132				
log likelihood	-17,254	-17,258	-16,582	-17,585	-17,931	-17,942	-18,256
AIC	34,517	34,522	33,173	35,178	35,867	35,886	36,515
BIC	34,542	34,541	33,205	35,203	35,879	35,892	36,521

The table shows maximum likelihood estimates of the parameters of the models. AIC is the Akaike information criterion and BIC is the Bayesian information criterion.

estimates suggest the following.

Result 4—Adaptive loss aversion: Subjects are initially loss averse and adjust their loss aversion in response to experience.

Support. For ALA, the estimate for the average initial loss aversion is 1.915. A value above one indicates loss aversion. The point estimate for w, the weight given to unanticipated losses and gains when updating loss aversion after trading, is 0.000547. A positive value indicates that, when the outcome of trading is better than anticipated, loss aversion decreases and vice-versa. In ALA loss aversion can vary whereas in CLA it is fixed. ALA has a better log-likelihood score but it also has one extra free parameter (w). The AIC and BIC measures of goodness of fit include penalties for the number of free parameters. On both these measures, ALA has a better (lower) score suggesting the better performance of ALA is not merely due to it having more parameters. CLA is nested in ALA which allows a likelihood ratio test to be used to test the null hypothesis that $w = 0$ against the alternative that $w \neq 0$. The test rejects the null hypothesis with a p-value of 0.0032. Hence, there is statistically significant evidence of adaptive loss aversion.

The size of the estimate of w and equation 5 suggest behavior adapts relatively slowly. Suppose, for example, $\lambda_t = 2$. If the agent receives an outcome 25 points better than anticipated, then $\lambda_{t+1} \approx 1.97$; if the outcome is 25 points worse than anticipated, then $\lambda_{t+1} \approx 2.03$. Note that relatively slow adaptive behavior is consistent with the observed evolution of bids shown earlier in Figure 3.

6.1 Alternative models

Five alternative models to ALA were estimated. They are variants of models drawn from the literature on behavioral game theory: quantal response equilibrium (QRE) (McKelvey and Palfrey, 1995), analogy-based expectation equilibrium (ABEE) (Jehiel, 2005), cursed equilibrium (CE) (Eyster and Rabin, 2005), level-*k* (Stahl and Wilson, 1994, 1995; Nagel, 1995), and experience-weighted attraction (EWA) (Camerer and Ho, 1999). The first three are equilibrium models defined by a fixed point of a function mapping from beliefs to actions. Level-*k* and EWA do not have an equilibrium defined by such a fixed point. In equilibrium models and level-*k*, bidding behavior is not updated in response to experience whereas in EWA, like ALA, it is.

QRE In this model, agents have correct beliefs about the expected utility from playing different actions but make errors (described by equation 8) when selecting actions. Given player *i*'s beliefs about the distribution of others' bids, the anticipated utility from each possible bid for player *i* can be calculated. Given the anticipated utilities and a value for the precision parameter γ, the distribution of player *i*'s bids can be found. Equilibrium occurs when all players are responding to their beliefs according to the logit function, and all players' beliefs are correct. The equilibrium distribution of bids σ_γ^* for a given value of γ can be found numerically. The likelihood of observed bids can be calculated using σ_γ^*. This, in turn, allows the maximum likelihood estimate of γ to be found by maximizing the following likelihood function.

$$L_i(\gamma) = \prod_t \sigma_\gamma^*(b_{it}) \tag{12}$$

ABEE This model combines Jehiel's analogy-based expectation equilibrium with QRE. In this model, the uninformed have coarse beliefs about the distribution of informed bids across the high and low states. They do not account for the informed conditioning their bids on whether a high state obtains. More precisely, when the true distribution of bids of the informed is $\sigma^*(b|\omega)$ with $b \in [1,100]$ and $\omega \in \{\omega_H, \omega_L\}$, the uninformed's beliefs $\mu(b|\omega)$ about the distribution of informed bids is given by the following.

$$\mu(b|\omega) = \Pr(\omega_H)\,\sigma^*(b|\omega_H) + \Pr(\omega_L)\,\sigma^*(b|\omega_L) \tag{13}$$

The model has one parameter, γ. ABEE predicts similar bidding patterns to QRE for symmetric information and for the informed under asymmetric information, but markedly different ones for the uninformed under asymmetric information.

CE This model combines Eyster and Rabin's cursed equilibrium with QRE. A cursedness parameter, $\chi \in [0,1]$, determines the extent to which the uninformed do not recognize that the informed have extra information. Using the same notation as used for ABEE above, the uninformed's beliefs $\sigma^*(b|\omega)$ about the distribution of informed bids is given by the following.

$$\mu(b|\omega) = \chi\left(\Pr(\omega_H)\,\sigma^*(b|\omega_H) + \Pr(\omega_L)\,\sigma^*(b|\omega_L)\right) + (1-\chi)\,\sigma^*(b|\omega) \tag{14}$$

Notice that when $\chi = 1$, CE coincides with ABEE, and that when $\chi = 0$, $\mu(b|\omega) = \sigma^*(b|\omega)$ implying CE coincides with QRE. With the estimated value of $\chi = 0.841$, the predicted bidding patterns are closer to ABEE than QRE.

Level-k This model combines level-*k* thinking with logit responses. Agents are allowed to have one of three levels of reasoning. Level 0 bid uniformly between 1 and 100. Level 1 respond to level 0 with logit errors. Level 2 respond to level 1 with logit errors. The model has four parameters (three are free): γ, $\Pr(k=0)$, $\Pr(k=1)$, and $\Pr(k=2)$. The following likelihood function was estimated.

$$L_i(\theta) = \sum_k \Pr(k|\theta) \prod_t \Pr(b_{it}|\theta, k) \tag{15}$$

EWA Camerer and Ho's (1999) experience-weighted attraction is applied as follows. Variables representing the attraction of bidding different amounts determine the choice of bids. $A_i^b(t)$ denotes player i's attraction for a bidding b in period t. The attractions are then used to calculate bid probabilities in the same way anticipated utilities are used in the other models.

$$\Pr(b_{it}) = \frac{\exp(\gamma A_i^b(t))}{\sum_{x=0}^{100} \exp(\gamma A_i^x(t))} \tag{16}$$

Players have a vector of 100 attractions for each information set they might encounter (symmetric information, asymmetric information uninformed, asymmetric information informed high state, asymmetric information informed low state). EWA does not specify what the initial values of the attractions are. For the purpose of estimating the model, the initial attraction $A_i^b(0)$ for each bid b was set equal to the expected payoff from biding b at the information set when all other bidders' bids are drawn from uniform distributions. Note that with these initial attractions, EWA makes the same predictions about first-round bidding as level-*k* does when all agents are level 1 and the same predictions as ALA does when $\lambda_1 = 1$.

As well as a set of attractions, each player has a variable $N(t)$ for each information set. This variable is used when updating attractions and can be thought of as measuring the amount of experience.

$N(t)$ and $A_i^b(t)$ are updated using the following equations.

$$N(t) = \rho N(t-1) + 1, t \geq 1 \tag{17}$$

The parameter ρ measures the rate that past experience depreciates.

Table 7: Alternative models

	ALA	CLA	EWA	Level-k	CE	ABEE	QRE
Logit errors	✓	✓	✓	✓	✓	✓	✓
Correct beliefs					partially	partially	✓
Equilibrium					✓	✓	✓
Heterogeneity	✓	✓	✓	✓			
Loss aversion	✓	✓					
Learning	✓		✓				

$$A_i^b(t) = \begin{cases} \frac{\phi N(t-1)A_i^b(t-1)+\pi_i(b,t)}{N(t)} & b = b_{it} \\ \frac{\phi N(t-1)A_i^b(t-1)+\delta\pi_i(b,t)}{N(t)} & \text{otherwise} \end{cases} \tag{18}$$

The parameter ϕ is the attraction depreciation rate. The function $\pi_i(b,t)$ gives i's payoff for bidding b in round t. The top expression in the piece-wise equation specifies how attractions for played actions get updated and the bottom one, how attractions for unplayed actions get updated. The expressions are the same except that forgone payoffs are weighted by parameter δ.

When EWA was estimated attractions were only updated if an agent traded (the same was true for updating loss aversion in ALA). This is because in the experiment, subjects could calculate the payoffs from unplayed actions after trading but not after not trading. There are five parameters to estimate: the precision γ, the initial weight given to attractions $N(0)$, the attraction depreciation rate ϕ, the experience depreciation rate ρ, and the weight given to forgone payoffs δ.

The results of estimating the models are shown in Table 6. The measures of fit allow their performance to be compared.

Result 5—Alternative models: Among the estimated models, EWA performed best followed by ALA.

Support. When the log likelihood score of the models is compared, EWA performed best followed by ALA. The ordering is the same even if it is based on the BIC or AIC, which both include a penalty for increasing the number of estimated parameters.

The key features of the models are summarized in Table 7. QRE is the only model where agents have correct beliefs about the joint distribution of other's actions and states of nature. In CE and ABEE, agents have correct beliefs about the marginal distribution of others' actions but not about the relevant joint distribution. In level-k, CLA, and ALA, agents have beliefs about the distribution of others' actions which typically are not correct. In EWA, beliefs are not defined. Among the estimated models, the following features are associated with better performance. First, relaxing the assumption of correct beliefs. Second, allowing non-equilibrium behavior. The four non-equilibrium models (ALA, CLA, EWA and level-k) outperform the four equilibrium models. A notable feature of the non-equilibrium models is that they allow for individual heterogeneity. In level-k, agents have different cognitive levels. In EWA, agents start with identical attractions for each action but these diverge as agents gain different experiences. In CLA and ALA, they have different initial levels of loss aversion. Finally, factors that differentiate the non-equilibrium models are loss aversion, learning, and whether learning carries over between games with different structures. EWA fits the data best, which suggests it is a good model to use in settings where agents repeatedly face instances of the same game. ALA performs better than the models without learning. An advantage of ALA over EWA is that it can be used in settings where agents face a series of games with different structures and in settings where payoffs from unplayed actions are unknown.

6.2 Data from experiments on the winner's curse

ALA is distinguished from some other learning models by two key features. First, the effects of experience can carry over between settings, such as between games with different structures or between information sets within a game. Second, it can be applied to settings where the payoffs from unplayed strategies are not available. One such setting is a sequential game where the second mover responds to the first mover. After playing the game, the first mover does not know how the second mover would have responded to a different first move, hence the first mover does not know the payoffs from unplayed strategies. Common value auctions and the acquiring a company task discussed in the introduction are natural games to study to explore these features. This section applies ALA and other behavioral models to data from Avery and Kagel's (1997) symmetric common value auction treatment and to data from Bereby-Meyer and Grosskopf's (2008) baseline acquiring a company game treatment.

Common value auctions In Avery and Kagel's baseline "symmetric" treatment, 23 bidders took part in a series of two bidder second price common value auctions. All of the subjects completed 18 auction rounds and 14 subjects returned to the lab and completed another 24 auction rounds. In each round, each bidder received an independent signal drawn uniformly from the range [1.00,4.00] with 1 cent increments. This meant there were 301 possible realizations of the signal, so bidders would rarely find themselves bidding at an information set they had encountered before. The common value of the item was simply the sum of the two bidders' signals. Bids were allowed in the range [0.00,10.00] with 1 cent increments, hence there were 1001 admissible values a bid could take.

The parameters of ALA, CLA, level-k, CE, ABEE and QRE were estimated using the same approach as described previously.

Result 6—Common value auctions: Among the estimated models, ALA and CLA performed best. Adaptive behavior is not detectable.

Support. The fit of the alternative models is reported in the top section of Table 8. For the common value auction data, ALA and CLA have approximately equal log likelihood scores. Accordingly, since it has one less parameter, CLA has slightly better AIC and BIC scores. As before, a likelihood ratio test can be used to test the null hypothesis that $w = 0$ against the alternative that $w \neq 0$. The null cannot be rejected for the common value auction data ($p = 0.4975$).

Acquiring a company In Bereby-Meyer and Grosskopf's baseline "Ball-100" treatment, 21 subjects played the role of buyer for 100 rounds with a computer playing the role of seller. As described in the introduction, the game involves the buyer making an offer to the seller for a company. The company is worth v to the seller and $1.5v$ to the buyer. The value of v is an integer distributed uniformly between 0 and 100 with the value known to the seller but not the buyer. Allowed offers were integers in the range [0,150], hence there were 151 admissible values an offer could take.

So far, agents in CLA and ALA, and the level 1 agents in level-k have been modeled as best responding to agents who bid all permissible values with equal probability. In the acquiring a company game, if a seller accepts all offers with probability 0.5, then the buyer's best response is to offer zero. It seems plausible that buyers might believe offering more would increase the chance of the offer being accepted while at the same time not appreciating that the seller's decisions depend on the seller's private information. Hence, level 1 buyers in level-k and all buyers in ALA were modeled as having the following beliefs about the seller's probability of accepting an offer b where the parameter $\eta \geq 0$ measures the seller's precision.

$$\Pr(accept|b) = \frac{\exp(b\eta)}{\exp(b\eta) + \exp(50\eta)} \tag{19}$$

The value of η was estimated with the other parameters of the models. When $\eta = 0$, all offers are accepted with probability 0.5. For moderate values of η, the probability of acceptance increases with the size of the offer. When η is large, only offers $b \geq 50$ are accepted. Note that the expected value of the company to the seller is 50, hence such beliefs are equivalent to believing the seller ignores their private information. Level 2 buyers in level-k were modeled as correctly believing the seller would use their private information about v when deciding whether to accept an offer.

Again, the parameters of ALA, CLA, level-k, CE, ABEE and QRE were estimated.

Result 7—Acquiring a company: Among the estimated models, ALA performed best. There is evidence of adaptive loss-aversion

Support. The results are shown in the bottom section of Table 8. Note that the estimates of η are greater than zero which is consistent with buyers believing higher offers have a greater chance of being accepted. For the acquiring a company task data, ALA performed best on all three measures (log likelihood, AIC and BIC). As before, a likelihood ratio test can be used to test the null hypot-

Table 8: Estimation using data from winner's curse experiments

	ALA	CLA	Level-k	CE	ABEE	QRE
Common value auctions						
precision, γ	0.156	0.156	0.098	0.088	0.088	0.082
mean of λ_1	0.667	0.697				
standard deviation of λ_1	0.773	0.801				
adjustment, w	0.000064					
level 0			0.074			
level 1			0.783			
level 2			0.143			
cursedness, χ				1.000		
log likelihood	-4,417	-4,417	-4,469	-4,504	-4,504	-4,608
AIC	8,842	8,841	8,947	9,013	9,011	9,217
BIC	8,855	8,855	8,965	9,022	9,015	9,222
Acquiring a company						
precision, γ	0.079	0.078	0.068	0.065	0.052	0.0002
mean of λ_1	1.280	1.508				
standard deviation of λ_1	1.989	2.040				
adjustment, w	0.000296					
buyer belief, η	0.164	0.162	0.163			
level 0			0.095			
level 1			0.905			
level 2			0.000			
cursedness, χ				0.996		
log likelihood	-9,447	-9,453		-9,752	-9,824	-10,533
AIC	18,905	18,913		19,509	19,649	21,069
BIC	18,933	18,936		19,520	19,655	21,075

The table shows maximum likelihood estimates of the parameters of the models. AIC is the Akaike information criterion and BIC is the Bayesian information criterion.

hesis that $w = 0$ against the alternative that $w \neq 0$. The null is rejected for the acquiring a company task data ($p = 0.0011$).

7 Discussion

ALA and the experiment were motivated by the conjecture that in markets people generally do not recognize that others may have different information and that loss aversion protects them to some extent from the losses they might otherwise incur. Loss aversion makes traders cautious about trading. The degree of loss aversion is adjusted after trading depending on whether the outcome of trading was better or worse than anticipated. The experimental results are consistent with previous studies in that under symmetric information there is a gap between WTA and WTP for lotteries and there is some evidence that this gap decays in a repeated market. The evidence for the decay of the WTA/WTP gap, however, is not as pronounced as in some previous studies. This could be because resolving the lotteries after trading made feedback noisier than in previous studies that used unresolved lotteries. The most important novel finding is the evidence of adaptive loss aversion. The version of ALA that allowed loss aversion to adjust fit the data better than CLA, the version in which loss aversion was fixed. Both ALA and CLA performed better than the variants of QRE, CE, ABEE, and level-k that were estimated on all the data-sets studied. However, ALA was outperformed by EWA on the data from the experiment reported in this paper. An advantage of ALA over EWA is that it can be used in settings where agents face a series of games with different structures and in settings where payoffs from unplayed actions are unknown.

ALA makes non-standard assumptions that at first sight may appear puzzling. Loss aversion is updated whereas beliefs about others' behavior are held fixed. One could argue it would be more natural to model changing behavior as due to updating beliefs about others' behavior. There are, however, at least two difficulties with this approach. The first concerns tractability. The joint distribution of other's actions and states of nature is a more complex object than a single variable representing loss aversion. For equilibrium models with consistent beliefs, this complexity is manageable since there is no need to update beliefs. For equilibrium models with partially consistent beliefs (ABEE and CE) and for level-k there is no updating of beliefs. This is despite the fact that average trading outcomes would have been inconsistent with beliefs. The difficulty is that to model out of equilibrium behavior, not only would the model need to specify agents' beliefs about the joint distribution and how they were updated, it would also need to specify agents' beliefs about how the distribution changes as others update their beliefs and hence change their behavior. The second concerns accounting for observed behavior. Previous studies have found WTA/WTP gaps decay in repeated markets. This can be readily accounted for by decreasing loss aversion. It is harder to account for in terms of updating beliefs about others' behavior. The experiments typically used dominant strategy elicitation mechanisms (so beliefs about others' behavior do not matter). Furthermore, Result 3 showed that bidding behavior was affected by lottery outcomes after trading. This even was the case when selling under symmetric information where the lottery outcome was neither informative about other traders' behavior nor affected the trader's earnings.[19]

When the fit of the seven models was compared, the models that performed better were ones with more parameters. Comparison of the AIC and BIC figures which include penalties for the number of free parameters suggests that the better performance is not due to over-fitting. Nevertheless, the better performing models are in some senses more complex. For example, ALA, CLA, EWA, and level-k all allowed individual heterogeneity whereas the equilibrium models did not. Most likely, the performance of the models could be improved by adding additional features. These features could include a tendency to place bids that are multiples of ten, a tendency for inertia (bidding the same value as in the previous round) or a tendency to adjust bids towards previously observed prices. Some degree of belief updating could be added to ALA. Whether such features are desirable depends on the research question being addressed. Indeed had the purpose of this paper merely been to model the average bidding shown in Figure 3, the extra complexity of ALA compared to CLA and level-k would be hard to justify based on the relative performance of the models. It is settings where behavior change is of interest that models like ALA are most relevant.

Turning to the implications of ALA, one might also wonder if the observed behavior, such as willingness to trade increasing when previous trading has had better than anticipated outcomes, would occur if the stakes were higher or the time period were longer. While it is hard to answer these questions decisively, there is evidence that, even over longer periods and when the stakes are high, personal experience influences behavior. For instance, Malmendier and Nagel (2011) find that people who have experienced low stock market returns throughout their lives so far are less willing to take financial risk, are less likely to participate in the stock market and invest a lower fraction of their liquid assets in stocks if they do participate.

What are the wider consequences of people behaving as predicted by ALA? The direct consequence is that there will be some potential trades that could make both parties better off but are not executed. This means that welfare gains from trade will not be fully realized. Furthermore, there are consequences to spillover effects. Suppose making a loss on a trade causes a person to be more loss averse and generally more reluctant to trade. Institutions that protect buyers from making losses on purchases will reduce the number of buyers suffering losses and, hence, loss aversion among buyers. Examples of such institutions include legal rights for buyers of goods, additional guarantees offered by some sellers, and financial redress for people who were mis-sold financial products. The results of this paper suggest the designers of such institutions face several challenges. Not only must the institutions alleviate the asymmetric information problem, they must also be attractive to people who are loss averse and do not recognize that others have different information.

[19]One might conjecture that changing bidding behavior is due to risk aversion decreasing as experimental earnings are accumulated. This could account for buying bids increasing over successive rounds. It could not account for the decay in selling bids typically seen in repeated market experiments. Neither could it explain first round behavior where selling bids exceed buying bids (implying sellers are less risk-averse) but buyers had higher incomes (in the experiment, buyers were endowed with 100 points and sellers were endowed with the lottery). Furthermore, the decay of the WTA/WTP gap is also observed in experiments where subjects are paid for one randomly selected round.

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